

Generative Adversarial Nets

Ian Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio. (2014)

GENERATIVE ADVERSARIAL NETS

In the proposed adversarial nets framework, the generative model is pitted against an adversary :



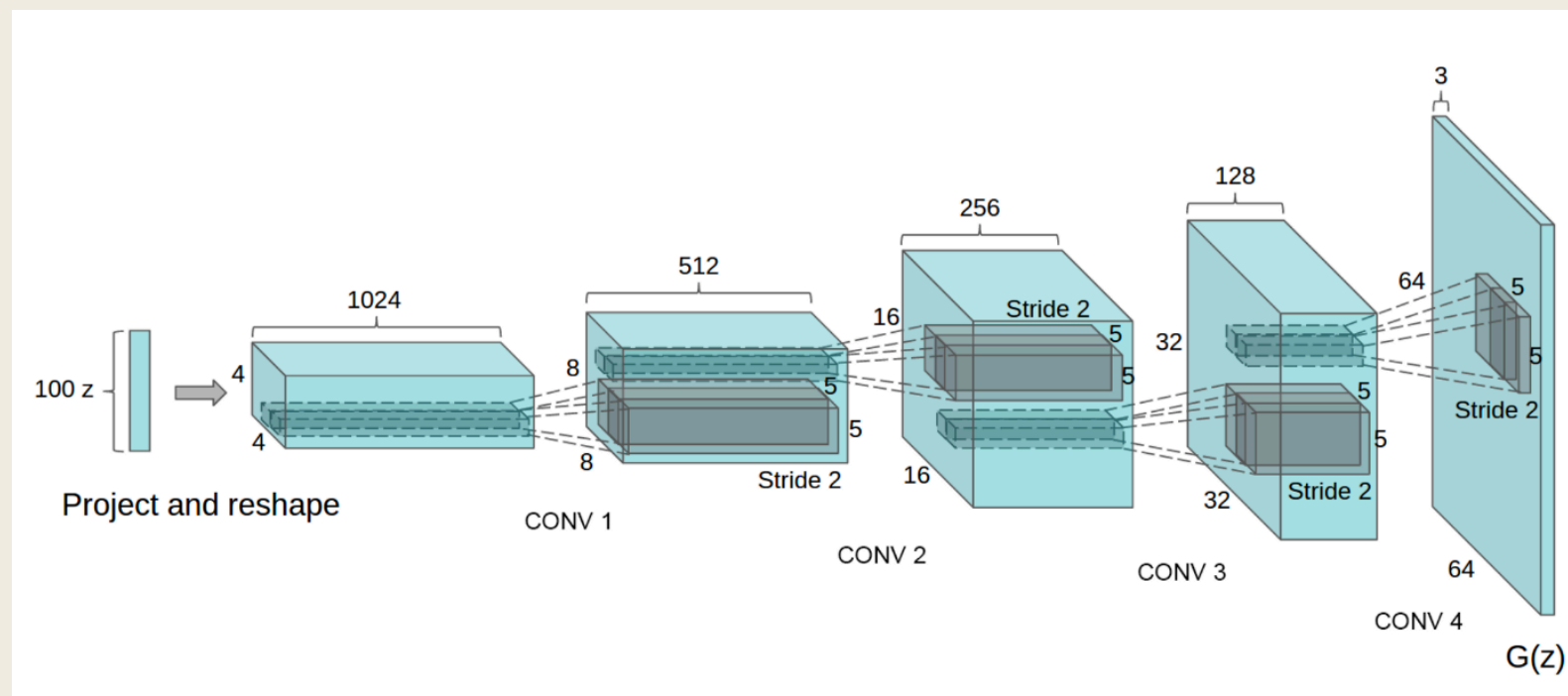
Generative model can be thought of as analogous to a team of counterfeiters, trying to produce fake currency and use it without detection.



Discriminative model is analogous to the police, trying to detect the counterfeit currency.

Competition in this game drives both teams to improve their methods until the counterfeits are indistinguishable from the genuine articles.

Generator

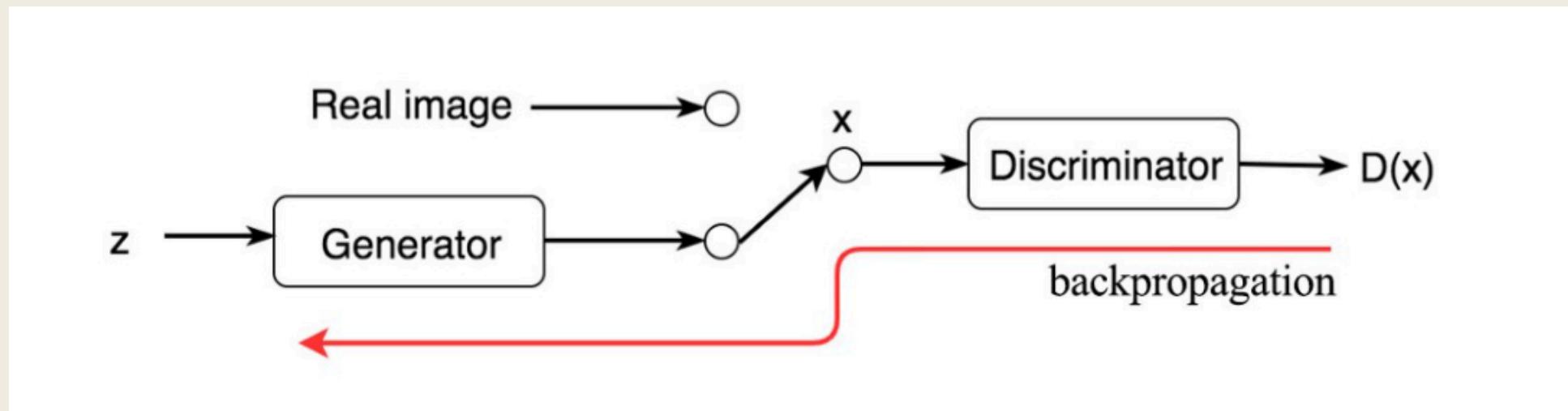


Multiple transposed convolutions are performed to upsample z to generate the image x . Deep learning clarifier in the reverse direction. (DCGAN)

How does generator create images?

- Noise z is sampled using normal or uniform distribution
 - z : input (color or shape of the image)
 - **$G(z)$ or x** : Generated image

Discriminator



If it is a generated image, $D(x) = 0$, if it is a real image, $D(x) = 1$

Discriminator determines whether the given image is real or generated - results in 1 if it's a real image, 0 if it's a generated image.

Then it sends back information / feedback as a critic.

Minimize $V(G)$

$$\min_G V(G) = \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]$$

Optimize G that can fool the discriminator the most.

Maximize $V(D)$

$$\max_D V(D) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]$$

recognize real images better

recognize generated images better

Resulting minimax game

$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))].$$

Pseudo-code for training GAN

Algorithm 1 Minibatch stochastic gradient descent training of generative adversarial nets. The number of steps to apply to the discriminator, k , is a hyperparameter. We used $k = 1$, the least expensive option, in our experiments.

for number of training iterations **do**

for k steps **do**

- Sample minibatch of m noise samples $\{z^{(1)}, \dots, z^{(m)}\}$ from noise prior $p_g(z)$.
- Sample minibatch of m examples $\{x^{(1)}, \dots, x^{(m)}\}$ from data generating distribution $p_{\text{data}}(x)$.
- Update the discriminator by ascending its stochastic gradient:

$$\nabla_{\theta_d} \frac{1}{m} \sum_{i=1}^m \left[\log D(x^{(i)}) + \log (1 - D(G(z^{(i)}))) \right].$$

end for

- Sample minibatch of m noise samples $\{z^{(1)}, \dots, z^{(m)}\}$ from noise prior $p_g(z)$.
- Update the generator by descending its stochastic gradient:

$$\nabla_{\theta_g} \frac{1}{m} \sum_{i=1}^m \log (1 - D(G(z^{(i)}))).$$

end for

The gradient-based updates can use any standard gradient-based learning rule. We used momentum in our experiments.

Possible Gradient Diminishing problem on the Generator

- The discriminator usually wins early against the generator
 - Easier to distinguish images in the early stages of training
- Solution :

$$-\nabla_{\theta_g} \log \left(1 - D \left(G \left(\mathbf{z}^{(i)} \right) \right) \right) \rightarrow 0 \quad \text{change to} \quad \nabla_{\theta_g} \log \left(D \left(G \left(\mathbf{z}^{(i)} \right) \right) \right)$$

Summary

- GAN is both supervised (discriminative) and unsupervised (generative) learning.
- GANs provide domain-specific data augmentation and solution to 'generative' problems such as image-to-image translation.

References

1. **Generative Adversarial Networks** Ian J Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron Courville, Yoshua Bengio. (2014)
2. **GAN - What is Generative Adversarial Networks GAN?** Jonathan Hui (Jun 20, 2018) Medium Article